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EVALUATE IMPROVEMENT IN ACCURACY OF BURNUP MODEL BY RELATING PLANFORM AREA TO FUEL MOISTURE CONTENT

Dr. Frank A. Albini

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MONTANA STATE UNIVERSITY
FS Contact: Ms. Elizabeth Reinhardt
Coop Contact: Dr. Frank A. Albini

IMPROVED CALIBRATION OF A LARGE FUEL BURNOUT MODEL

Frank A. Albini* and Elizabeth D. Reinhardt+

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* Research Professor
Dept. of Mechanical & Industrial Engineering
Montana State University
Bozeman MT 59717-3800

Telephone (406)994-6298
FAX (406)994-6292
umefa@msu.oscs.Montana.edu

+ Research Forester, USDA Forest Service
Intermountain Fire Sciences Laboratory
P. O. Box 8089
Missoula MT 59807 /s=E.Reinhardt/ou1=s22L01a/pd=usda.fs.x400/c=us@mhs-fswa.attmail.com

Telephone (406)329-4836
FAX (406)329-4877

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ABSTRACT

Calibration and testing of a computer simulation of the burning of large woody natural fuels has been presented previously in this journal. This note describes an improved calibration of the model for better prediction of fuel loading reductions. Using the same data as before, fuel consumption predictions are improved substantially by making the area influence factor a function of fuel moisture content.

INTRODUCTION

A computer simulation of the burning of large woody natural fuels has been developed [Albini 1994, Albini and Reinhardt 1995, Albini, Brown, Reinhardt and Ottmar 1995]. A firm objective in fashioning the simulation was to represent the physical processes that control ignition, rate of burning, and extinction of the fuels in a logically consistent construction, using simple but heuristically defensible models. In this simulation the burning rate of each fuel element is calculated from its thermophysical properties, moisture content, and the rate of heat transfer to it, taking into account the local fire intensity which it experiences as a function of time.

Two empirical constants, r_0 and dr, are used in the simulation to model how the local fire intensity is affected by the interaction of fuel elements due to physical proximity. Values for these parameters were determined by matching simulation predictions to measurements of laboratory wood crib burning rates [Anderson 1990, Albini and Reinhardt *op cit*]. Another empirical constant, K_a, affects the assignment of interaction partners for the fuel elements. The main influence of this parameter is upon the prediction of ultimate fuel consumption, the fire intensity history being largely insensitive to the choice of its value. In this note we describe a recalibration of the simulation, with K_a made a function of fuel moisture content. This revision improves the model's predictions of large woody surface fuel consumption. Here we recap the role of this parameter in the model and offer our rationale for making it a function of fuel moisture content. For a more thorough discussion see Albini and Reinhardt [1995].

Accounting for the interaction between burning surface fuel elements is crucial to the fidelity of the simulation. Anyone who has witnessed the burning of wildland fuels in the field, built a picnic bonfire, or tended a fire in a fireplace recognizes that large woody fuels burn in isolation with little vigor and incompletely, if at all. But a fuel element which alone will burn not at all, may, if in close proximity to other sufficiently dry fuel elements of similar physical size or smaller, burn with considerable vigor. This phenomenon we attribute to the exchange of radiation between the burning solid surfaces and the

formation of a shared stream of gaseous pyrolyzate fuel that burns in the space between the interacting elements. The model simulates the locally increased fire intensity due to this interaction by modifying the values of r_0 and dr. The rate of burning of each fuel element is calculated using a semi-empirical model of burning rate as a function of local fire intensity and the thermophysical properties of the fuel element [Albini and Reinhardt *op cit*].

But the model must also determine the extent to which fuel elements of each size class interact with one another. In the simulation we have constructed this is done by dividing the loading of each size class into fractions that interact with each size class the same and smaller (to avoid double counting) and with no other surface fuel. The latter fraction is presumed to interact with smouldering duff. The empirical parameter K_a plays an important role in evaluating the pairing fractions. We define an "effective interaction area" as that area surrounding the centerline of a fuel element's planform projected area (length x diameter) within which the planform area of another element of the same size or larger would result in its burning rate being influenced by the first element. The effective interaction area is the product of K_a and the planform area of each fuel element. The model assigns the interaction fractions of each fuel loading on the basis of expected fractional overlap of planform areas with effective interaction areas, assuming fuel elements to be randomly but uniformly strewn over the burn site. Only binary interactions are considered; multiple overlaps are neglected.

In the calibration effort previously reported [Albini, Brown, Reinhardt and Ottmar *op cit*], measurements of the consumption of woody surface fuels in prescribed fires were compared to model predictions of same, using various values for the parameter K_a. This allowed selection of a "best" value for the parameter. But a disturbing divergence of error trends and model error sensitivities amongst the various data sets was noted and discussed, and the performance of the model in predicting total surface fuel consumption was disappointing. We revisited this issue in the research documented here, finding that model performance in predicting fuel consumption is substantially improved by making K_a a simple function of fuel moisture content

MODEL REVISION

All other things being kept the same, K_a would be expected to vary with fuel condition, such as state of decay, presence or absence of bark cover, and moisture content. These attributes influence the radiative characteristics of the fuel surface and the relative transparency of the gaseous pyrolyzate to radiation (infrared absorptivity of air depends strongly on its water). The influences of these factors and other fuel properties such as specific heat capacity, heat of combustion, thermal conductivity, temperature of peak pyrolysis rate, etc., are explicitly accounted for in the physical simulation of the rate of combustion and calculation of fire intensity. It was found in our early investigations that the presence or absence of bark had little influence on ignition delay or burning rate [Albini and Reinhardt, *op cit*] and we believe that the principal influences of decay are reflected in lower ignition temperature and reduced temperature of peak rate of pyrolysis. In the interest of simplicity, and because we believe that this property is the most influential one, we modeled K_a as a function only of fuel moisture content.

The variation of K_a with moisture content (M) which we expect is that K_a should have its maximum value at low moisture content, be relatively insensitive to small changes in moisture when dry, to be down sharply at 30% (fibre saturation) moisture content, and to be essentially zero in the neighborhood of 50% (fresh green wood). From experience with laboratory crib burns, pile burns, and bonfires, we would expect the peak value of K_a to be about 3. That is, a piece of dry wood would have an enhancing effect on the burning of another piece of dry wood of the same size if the two are placed so that their surfaces are no more than about a diameter apart. But if one of the pieces is saturated with moisture, we would expect that they would have to touch or physically overlap to interact. And if one is fresh green wood, we would expect little or no interaction, even if the two pieces were placed one atop the other. So we posit a bell-shaped curve for $K_a(M)$ and seek a functional form with a small number of parameters and the general features described. The Gaussian or normal probability distribution function has the characteristics we seek and requires only two parameters: The value at $M = 0$, and a parameter that controls its decline with increasing M.

In this effort we revisit the data sets used previously, from Deception Creek [Reinhardt, Brown, Fischer, and Graham, 1991], Lubrecht [Norum 1975, 1976], and PNW [Sandberg and Ottmar 1983] and recalibrate the simulation using for K_a a function of fuel moisture content of the form

$$K_a = K \exp(- B M^2) \qquad (1)$$

where M is the moisture content, fraction dry mass, of the smaller (or same size) of the interacting fuel elements and parameters K and B are empirical constants to be determined. In exercising the simulations the same data and procedures were used as in the previous calibration, with the following exceptions:

1) The duff moisture content for each burn unit was adjusted so that the prediction of duff consumption built into the simulation [Brown, Reinhardt and Fischer 1991] would result in the measured average value for that site. This eliminates one source of variability and allows us to attribute more of the variation in fuel consumption to the influence of surface fuel moisture.

2) Two burn units (North Scotty and North Scotty 22) were culled from the PNW data set because their simulations yielded such large errors of overprediction that their inclusion would have contaminated the parameter selection process. Anyone who has dealt with field data is familiar with the problem of atypical samples. Such "outliers" can sometimes be explained by variations of uncontrolled influences, but are often eliminated for the pragmatic reason that they represent results that are atypical or unexpected and therefore not proper fodder for modeling. By discarding the data from two of 70 burns, we acknowledge that the model may be expected to overpredict fuel consumption significantly in about 3% of the cases. But the quality of the predictions in the other 97% of the cases we know will be much better than would have been the case had we retained the two atypical samples.

3) All the data were considered at the same time, rather than selecting a subset for calibration and using the remainder as a test set as was done in the first calibration. This was done as a matter of

convenience, because testing model performance required long run times which meant the PC could be used for nothing else during these calculations. The model runs simulated about 10 hours of burn time using 10 s time steps, so each burn required several minutes of PC run time. In all more than a thousand hours were spent with the PC dedicated to this task.

CALIBRATION AND TEST

The three data sets were processed and examined separately, as was done before. The mean and mean squared errors of predicted fuel consumption were then combined to guide the selection of parameters K and B in a disciplined search for a global minimum of the sum of squared errors of prediction. The initial parameter ranges were

$$K = 0.5 (0.5) 5.0 \quad , \quad B = 5.0 (5.0) 50 \tag{2}$$

Figures 1 and 2 exhibit the behavior of the mean and mean squared errors of prediction with variation in B for the three individual data sets and for all data combined, using K = 0.50 and 5.00 respectively. Errors are sensitive to the value of B only for the larger values of K but the mean squared error for all data exhibits a minimum with both K and B.

The search ranges were systematically collapsed about the minimum squared error in a series of steps, with the final sweep restricted to

$$K = 2.75 (0.25) 3.75 \quad , \quad B = 16 (2) 24 \tag{3}$$

resulting in selection of the "best" model for K_a as:

$$K_a = 3.25 \exp(- 20 M^2) \quad (4)$$

No finer scale search was deemed to be justified given the accuracy of data and model limitations.

Note that the moisture content dependence in this expression reduces the value of K_a to about 0.54 when M = 0.30 (near fibre saturation) and to 0.02 when M = 0.50, as expected from the heuristic arguments presented above.

Figure 3 shows the local mean squared error variation with B for all data, using K = 3.00, 3.25, and 3.50. Figures 4 - 7 are scatter plots of predicted and observed fuel consumption for the three data areas and for all data combined. Table I shows mean and mean squared errors of model predictions of the fuel consumption for all 68 burn sites, using the same values of K and B as in Figure 3. But in this table, mean errors of prediction are normalized by sample mean fuel consumption (4.77 kg / m^2) and mean squared errors are normalized by the variance (5.95 kg^2 / m^4).

PERFORMANCE IMPROVEMENT

The data of Figures 4-7 and Table I indicate that model performance has been improved significantly by this reformulation. Figure 4 shows a slight underprediction bias for the Deception Creek data and figure 6 shows a somewhat larger overprediction bias for the PNW data. Both these biases were evident in the previous calibration, but were of greater magnitude. In both the present and the previous calibrations, the Lubrecht data were well predicted by the model.

The performance of the model using all 68 burn sites, summarized in Table I, shows a negligible overprediction bias of about 6% of the sample mean. The mean squared error of prediction is about 29% of the variance in this instance. In the previous calibration exercise, the "best" value for K_a yielded a

mean squared error of 47% of the variance for the entire data set. More importantly, in the previous calibration, the compromise "best" K_a value balanced a large overprediction bias for PNW data against an underprediction bias for Deception Creek data. Although mean and mean squared prediction errors were improved in the previous calibration exercise when certain of "outlier" burn sites were culled from the data, the model performance could not be improved to near the level of the present calibration results. In the present effort the various data sets are better predicted individually and there exists a clear two-parameter minimum in the mean squared error of prediction for the entire data set.

Recalculation of the weight histories of burning laboratory cribs used to determine the parameters r_0 and dr confirmed that these simulations were essentially unchanged by this revision to the model. This was expected because the crib fires were conducted at extremely high loadings. This condition makes the simulation sensitive to the parameters r_0 and dr but insensitive to the value of K_a.

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TABLES AND FIGURES

Figure 1a. Mean errors of predicted fuel consumption for K = 0.50.

Figure 1b. Mean squared errors of predicted fuel consumption for K = 0.50.

Figure 2a. Mean errors of predicted fuel consumption for K = 5.00.

Figure 2b. Mean squared errors of predicted fuel consumption for K = 5.00.

Figure 3. Mean squared errors of predicted fuel consumption, final variable search.

Figure 4. Predicted and observed fuel consumption for Deception Creek data.

Figure 5. Predicted and observed fuel consumption for Lubrecht data.

Figure 6. Predicted and observed fuel consumption for PNW data.

Figure 7. Predicted and observed fuel consumption for all data combined.

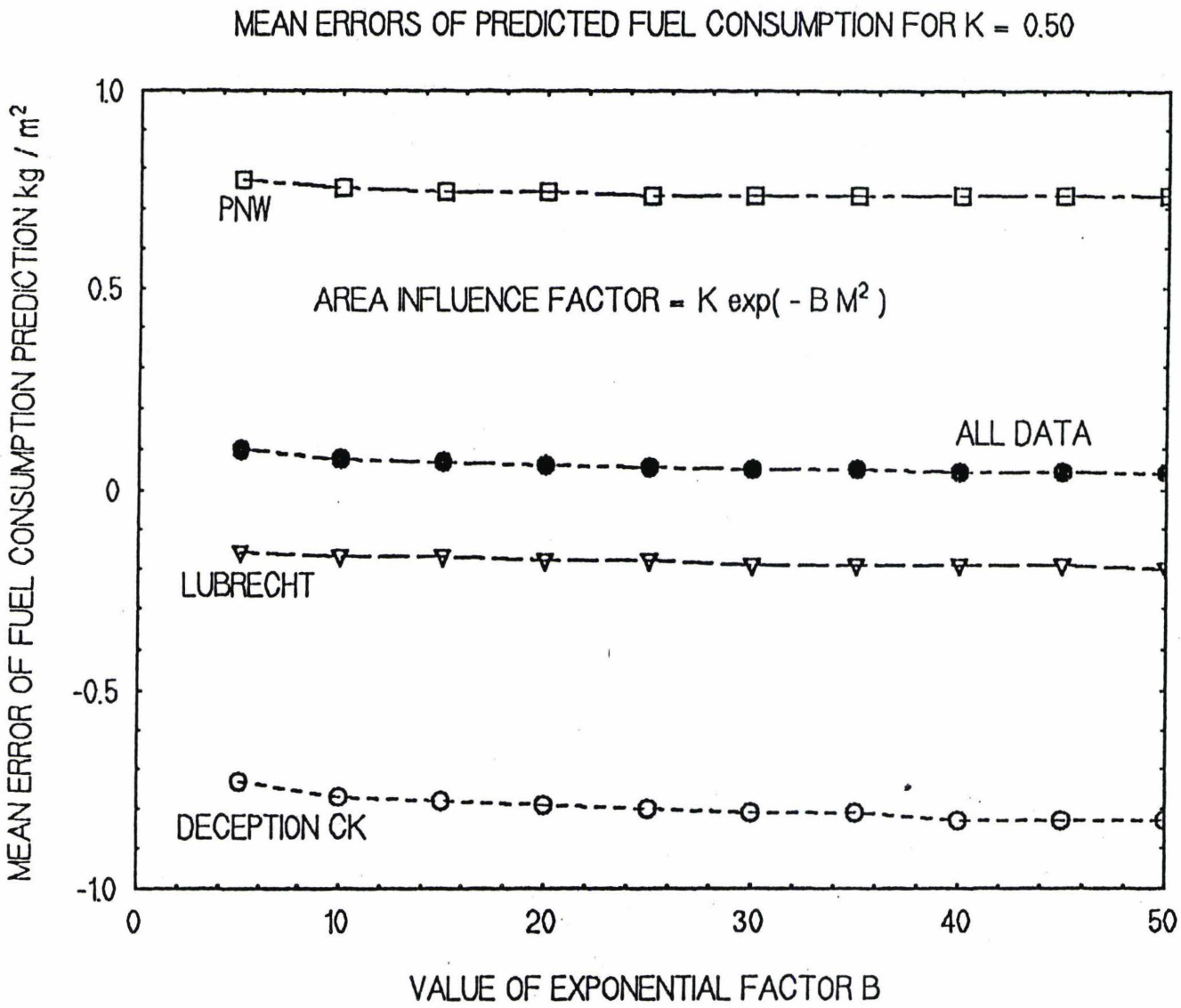

Figure 1a. Mean errors of predicted fuel consumption for K = 0.50.

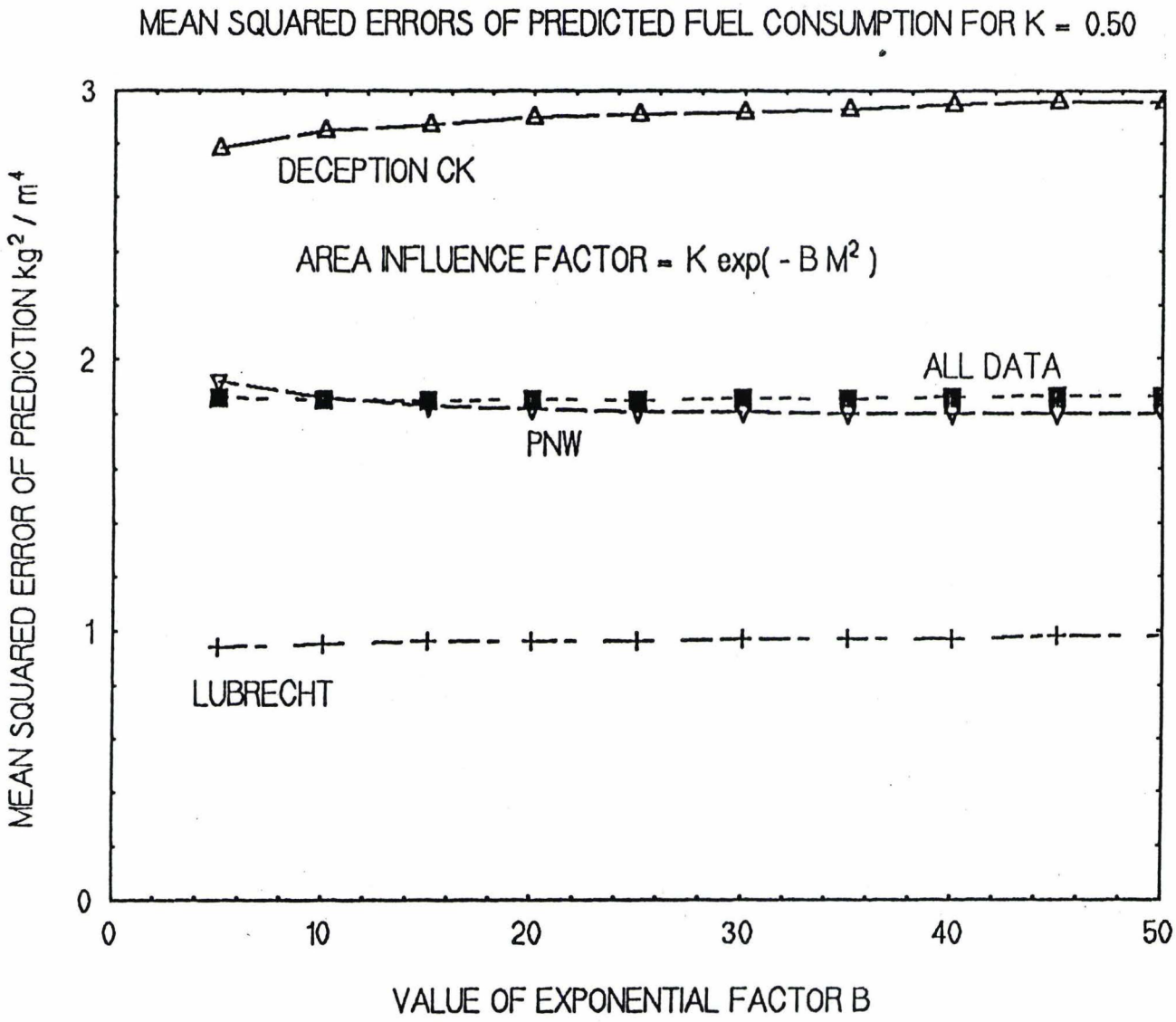

Figure 1b. Mean squared errors of predicted fuel consumption for K = 0.50.

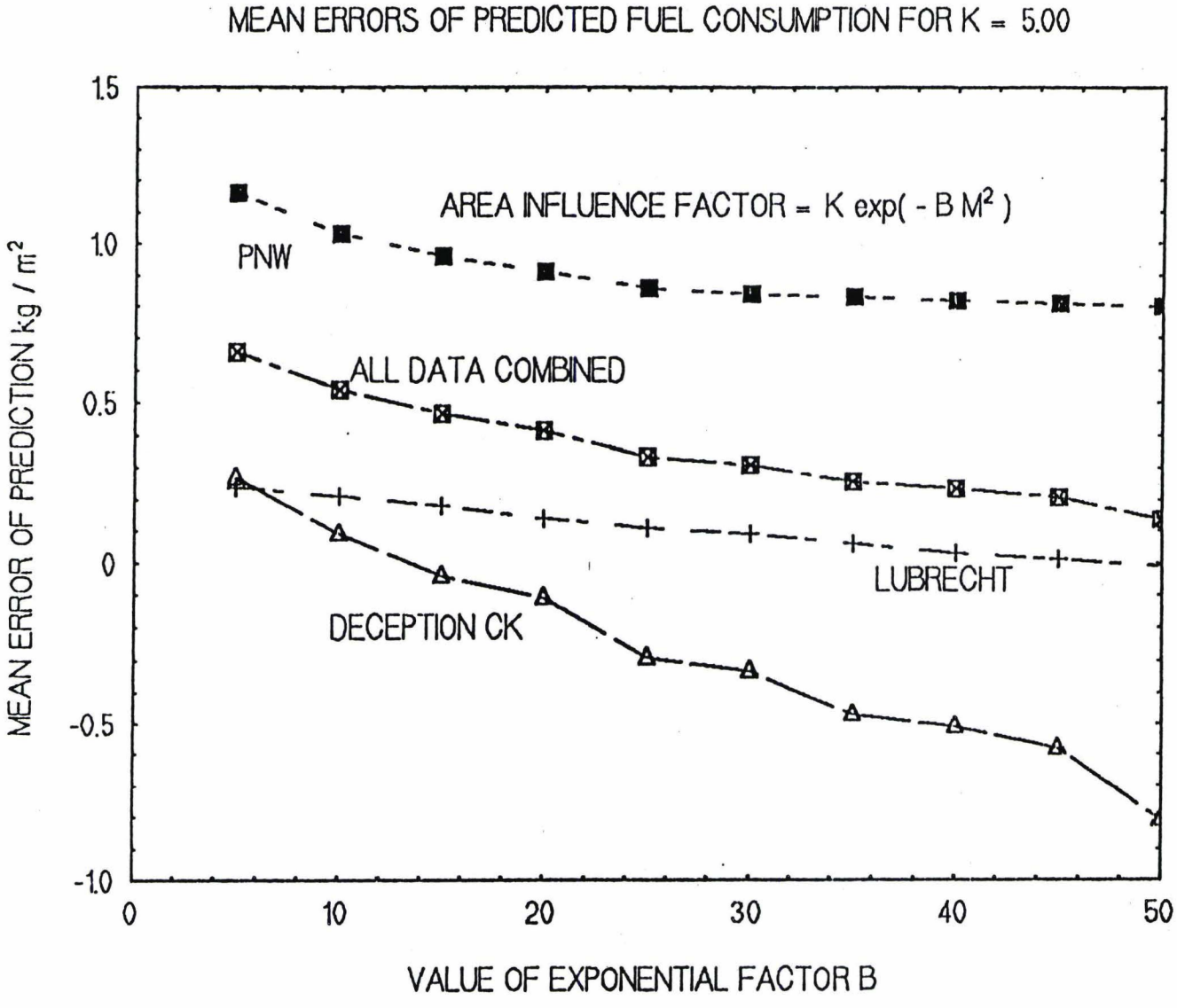

Figure 2a. Mean errors of predicted fuel consumption for K = 5.00.

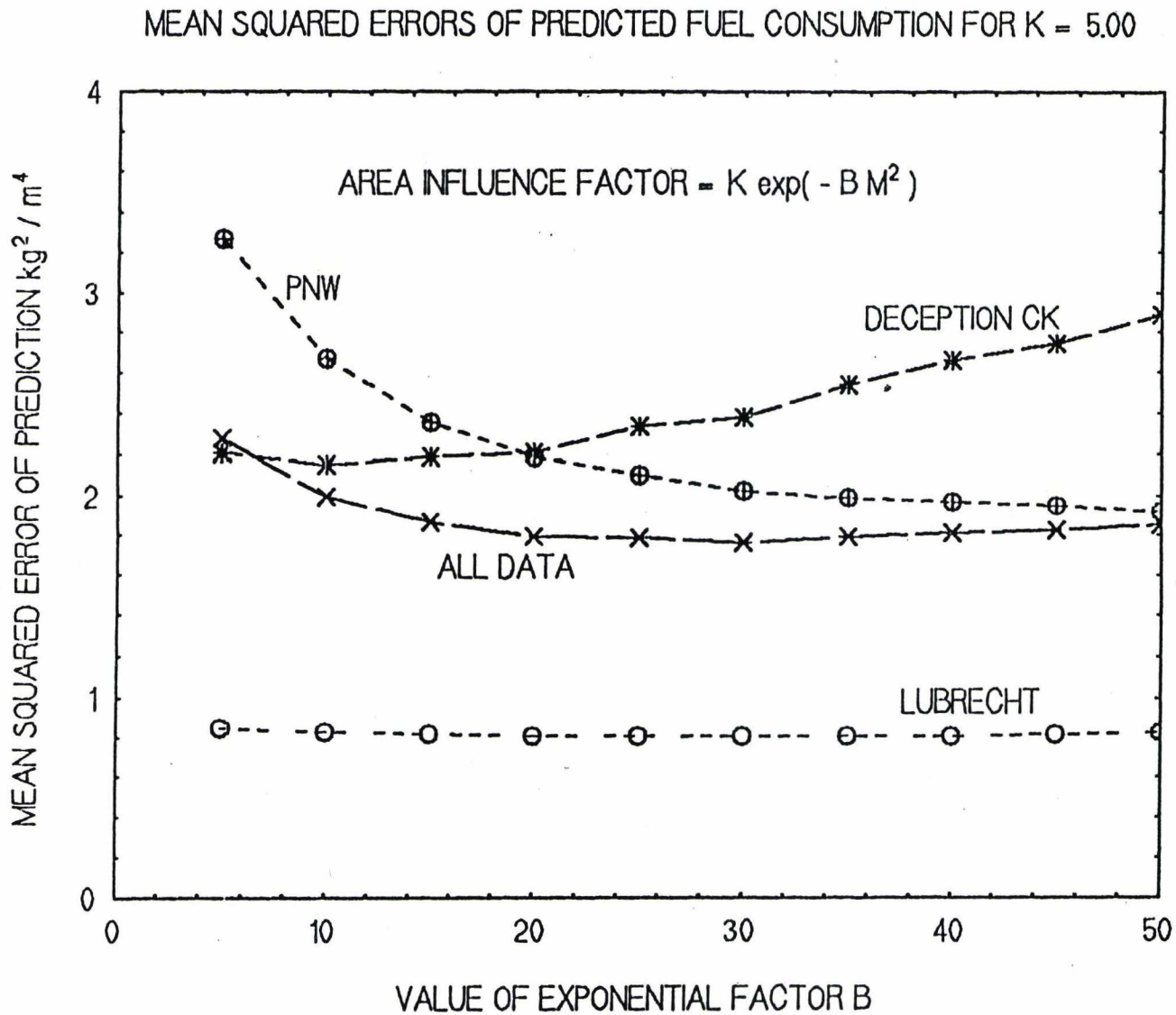

Figure 2b. Mean squared errors of predicted fuel consumption for K = 5.00.

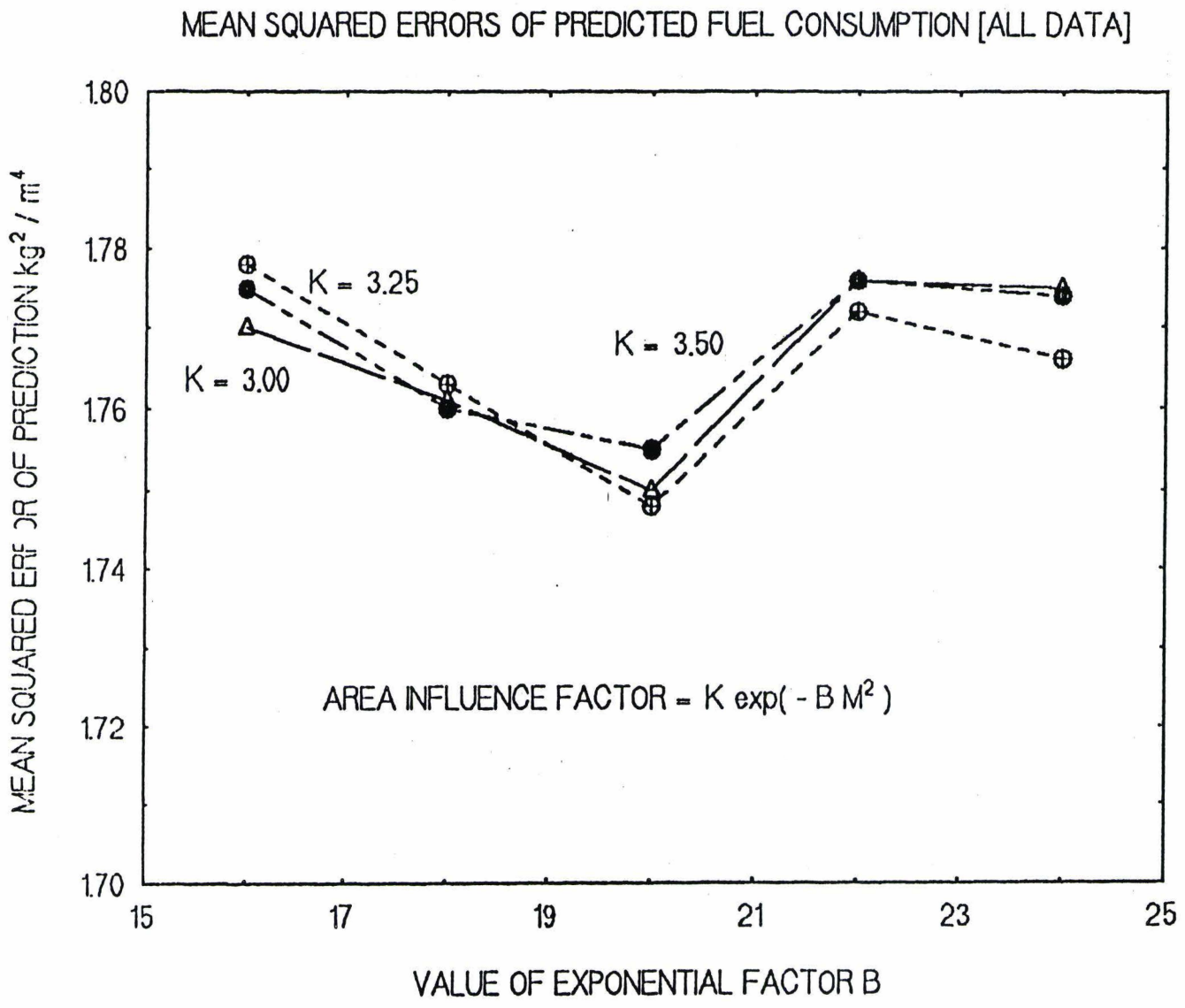

Figure 3. Mean squared errors of predicted fuel consumption, final variable search.

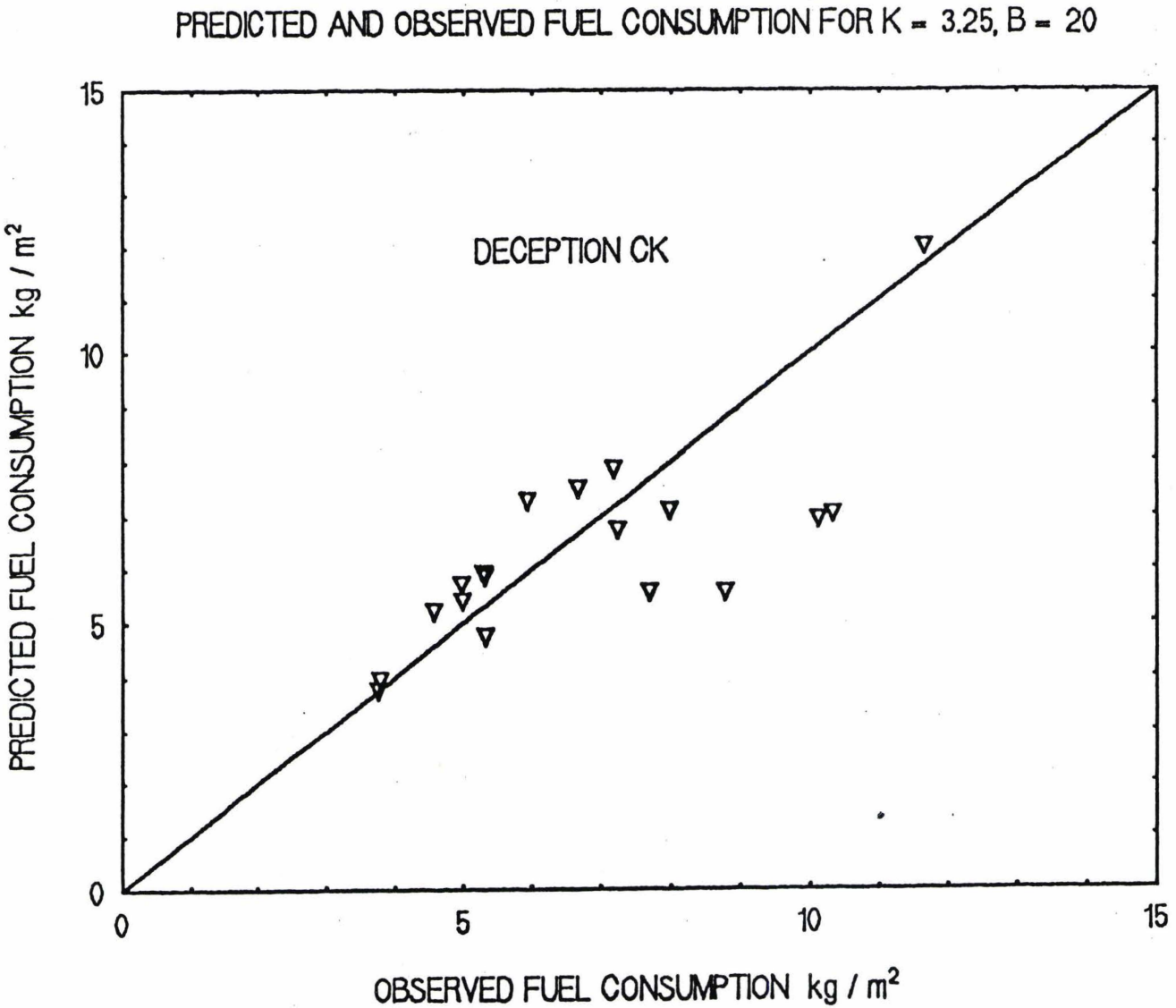

Figure 4. Predicted and observed fuel consumption for Deception Creek data.

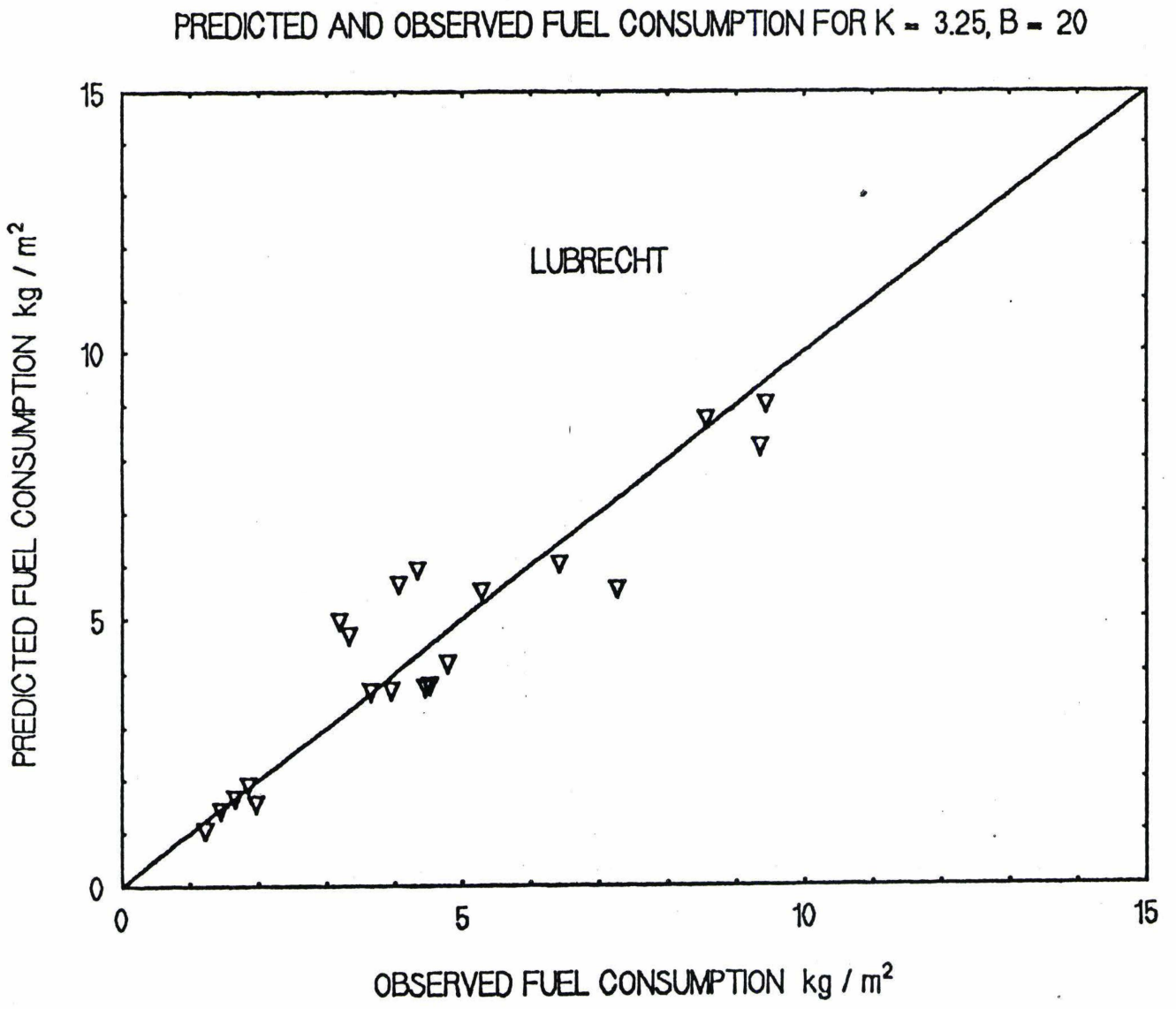

Figure 5. Predicted and observed fuel consumption for Lubrecht data.

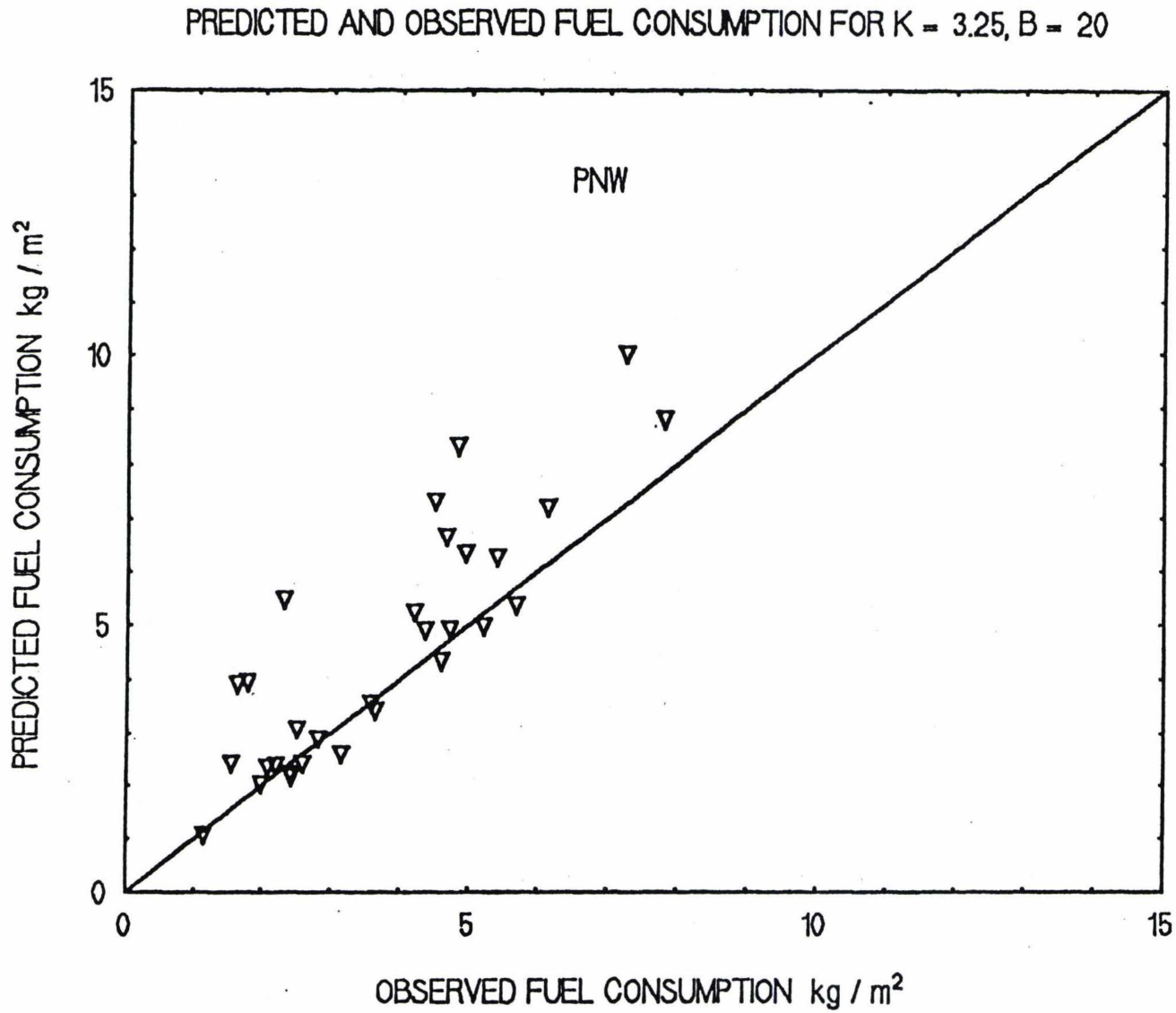

Figure 6. Predicted and observed fuel consumption for PNW data.

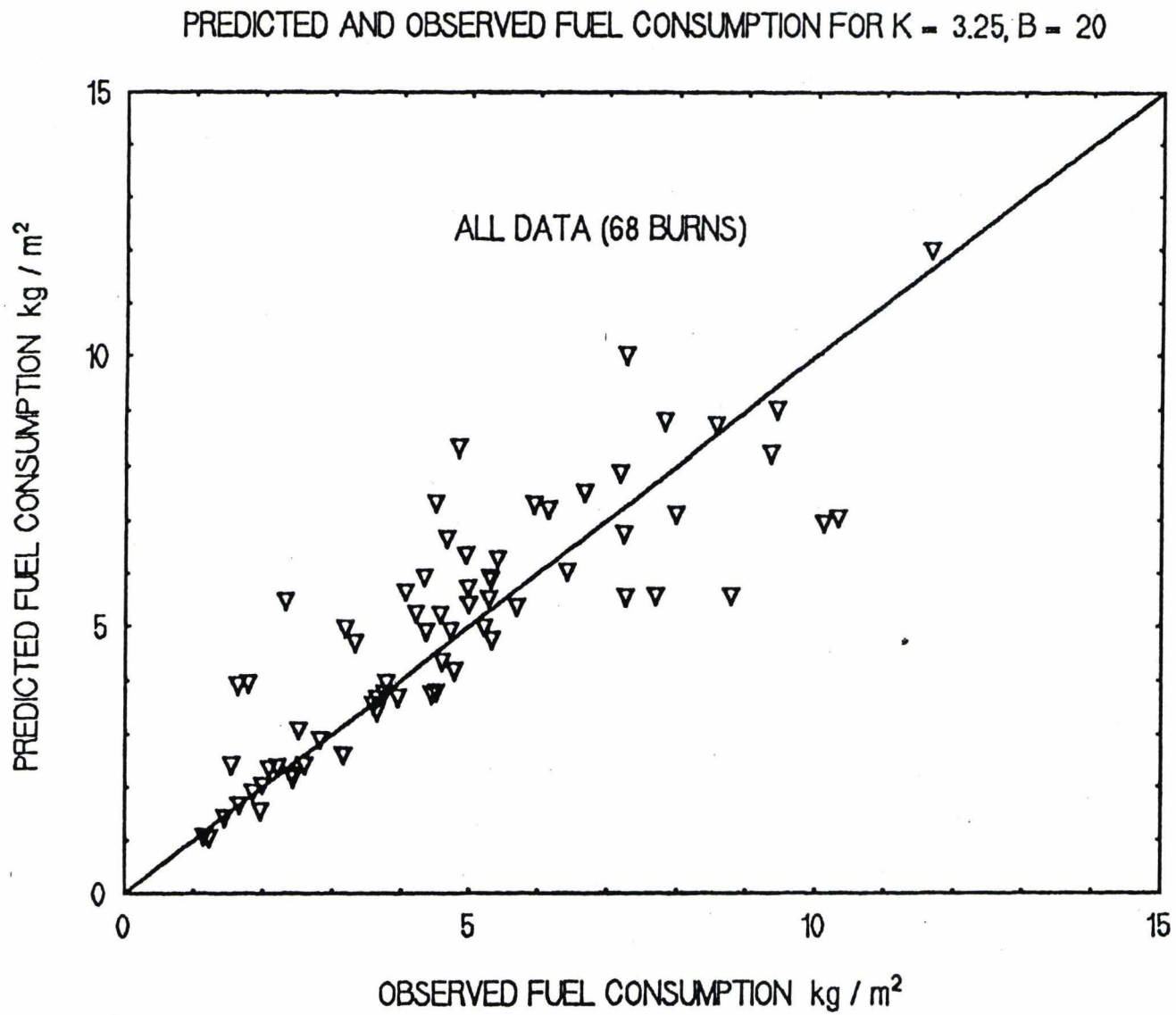
PREDICTED AND OBSERVED FUEL CONSUMPTION FOR K = 3.25, B = 20
ALL DATA (68 BURNS)
PREDICTED FUEL CONSUMPTION kg / m²
OBSERVED FUEL CONSUMPTION kg / m²
0
5
10
15

Figure 7. Predicted and observed fuel consumption for all data combined.

	Mean error / mean consumption			Mean squared error / variance		
Value of B	K = 3.00	3.25	3.50	3.00	3.25	3.50
16.0	.060	.065	.070	.298	.299	.300
18.0	.057	.062	.065	.296	.297	.297
20.0	.055	.059	.063	.294	.294	.294
22.0	.049	.053	.056	.299	.298	.298
24.0	.047	.051	.053	.299	.297	.298

Table I. Mean error of predicted fuel consumption normalized by mean fuel consumption (4.77 kg / m^2) and mean squared error of predicted fuel consumption normalized by variance of fuel consumption (5.95 kg^2 / m^4) for 68 burn sites. Final parameter values selected for model use were K = 3.25 and B = 20.